Worker Heterogeneity in Career Dynamics

Madhurima Chandra*

Abstract

This paper documents and studies heterogeneity in career progression by gender in the German context, using survey data that allows us to measure career ladder movement over the life cycle and also utilize detailed information on individual characteristics. I look into the potential role of differences in individual characteristics in determining career progression - working full-time or part-time, presence of children, marital status, working in private or public sector, and industry of employment, separately for women and men. Life cycle career profiles reveal large gender differences by these characteristics. Conditional estimates for the first three factors point towards penalties for women's careers, whilst showing no significant association or at times, a premium, for the career dynamics of men. The public sector appears to not be associated with higher promotion rates, however it offers a premium in average job level for both genders, likely explained by workers in this sector starting their careers at a higher job level. Oaxaca-Blinder decompositions at different stages of the life cycle allow us to trace the evolution of this gender gap, as well as that of its unexplained and explained components, over the life cycle. I find evidence of a gap in mean job level that cannot be accounted for by the aforementioned characteristics, which comes up around age 30-35 and persists over the remainder of the career life cycle. This is noteworthy in light of the fact that I account for the presence of children. Dynamic effects of childbirth are not captured in the decomposition analysis however, which may account for at least some fraction of the unexplained gap.

*mchandra@uni-bonn.de

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1 Introduction

Men and women fare differently in their labor market outcomes over the life cycle. A large body of literature has been dedicated to studying this gender gap, with most papers focusing on wage rate differentials. A smaller subset of the literature looks at gender career advancement gaps, with significant heterogeneity in defining what constitutes career advancement or a promotion, and (likely as a result) also in findings. This paper, closely related in spirit to studies on gender promotion gaps, defines promotions and demotions directly from observed movements along the career ladder and examines worker heterogeneity in life cycle career dynamics by gender.

Increasing gender gap in wages over the life cycle can largely be attributed to widening differences in career ladder progression. Bayer and Kuhn (2020) show that this explains almost half of the increase in the gender wage gap over the life cycle. Bronson and Thoursie (2018) decompose life cycle wage growth and find that promotions explain around 40-45% of wage growth between the ages of 25 to 45, for both women and men.[1] Building on this established empirical fact, in this paper I zoom in on the aspect of career ladder dynamics. How different do life cycle career progression trajectories look for women and men? Do these systematic differences in career dynamics persist when we condition on differences in individual, family and job characteristics? How do each of these factors associate with the career progression of women and that of men? How does the gender gap in career dynamics evolve over the life cycle? Do the aforementioned factors collectively account for the observed gap, or does a fraction remain unexplained? These are the questions I seek to address in this thesis.

This study utilizes the German Socio-Economic Panel (SOEP) data (Schupp et al. (2017)). This data allows us to directly measure movement up and down the career ladder, and also provides detailed information on human capital attainment, family circumstances and job-related characteristics at the individual level. Importantly, the panel dimension of our data enables us to accumulate promotions and demotions at the individual level, providing us an opportunity to observe net career progression at each stage of the life cycle for every individual. This allows us to directly relate career ladder dynamics to these individual characteristics, and document significant gender differences in these associations.

In studying promotion dynamics, this paper focuses on both the *job level* and *cumulative net career progression* (or *cumulative net promotions*) of individuals at each stage of the life cycle. As described in Bayer and Kuhn (2020), *job levels* are tied to the "autonomy, responsibility, and complexity in executing a job's tasks and duties". They represent the intensive margin of task execution (how tasks are done), whereas occupations can be thought of as serving the extensive margin. *Cumulative net career progression* provides a cumulative measure of (net) steps climbed on the career ladder, taking into account

[1] Note that their definition of promotions differs from ours. They define promotions as large wage jumps relative to the individual's co-workers at the same firm. Our measure of promotions (demotions) relies on observed movements up (down) along the career ladder.

total promotions and demotions experienced till each age. Section 2.1 provides detailed descriptions of both variables.

The study starts by documenting significant gender differences in (cumulative net) career progression over the life cycle. First I present the unconditional differential using life cycle career progression profiles for men and women, which suggests that promotion dynamics by gender start diverging from the beginning (age 25). This is complemented by conditional estimates of the gender career progression gap, which provides further evidence of the gap prevailing even after controlling simultaneously for a rich set of background characteristics.

To study the gender gap in (upward) career ladder movement further, I look into the potential role of differences in individual characteristics in determining career progression: working full-time or part-time, presence of children, marital status, working in the private or the public sector, and industry of employment - separately for women and men. In studying each of these factors, I first look at the cumulative net promotion profiles for each gender to get a sense of the unconditional gap, and next attempt to provide conditional estimates of the penalty (or premia) each of these factors may possibly have for women's and men's career dynamics.

In looking at differences by full-time and part-time participation in the labor force, I first document that though the share of women engaged in part-time work is indeed far larger than men, a comparison of women and men engaged in full-time work (throughout their life cycle) reveals the gender net-promotions gap to still persist (though it is lower than the difference between all men and women). This provides evidence for part-time differences not fully accounting for the systematic gender differences in career progression. Next, I focus on within-women groups and document that part-time work is likely associated with lower promotions, relative to women working full-time. I present estimates of a part-time penalty on cumulative net career progression for women, conditioning on a broad set of observables.

Next, I take a close look at the effect of children on promotion dynamics of women and men. Career profiles by years relative to first childbirth provide striking evidence of a sharp fall in career progression for women after the birth of their first child. This points to dynamic effects of childbirth being strongly associated with career progression of women. Next, in studying the relation between having (one or more) children and an individual's *job level*, I compare women with children to those without, and present a similar comparison for men. I find evidence of presence of children being associated with a penalty for career dynamics of women, whilst displaying a premium for men. This is corroborated in both, life cycle career profiles as well as in conditional estimates.

The third factor of interest is marital status which shows large gender differences between married women and men when looking at cumulative net promotion profiles over the life cycle. On conditioning on numerous background characteristics (education levels, work experience, birth cohort, age, survey year, presence of children and also industry

and occupation) being married itself appears to have no significant association for men's career dynamics. For women, I find evidence that accounting for sorting into industries and occupations (likely those amenable for flexible hours), and presence of children, mostly explain the gap in career progression between married and non-married women.

Most of the analysis focuses on private sector employees aged 25-55. In looking at differences by public-private sectors (and later by industries), I additionally include public sector employees in my sample. I note descriptively that on average, men and women in the public sector are consistently on a slightly higher job level than their private-sector counterparts, for all age groups. This fact appears to be particularly relevant when looking at conditional estimates of the public-sector premia on career dynamics for men and women. Though we see no significant conditional effects of being in the public sector (for both men and women) on cumulative net promotions, but focusing on the *job level* reveals a premium relative to being in the private sector. This public-sector premium holds for both men and women, with men seeing a higher level. This points to workers in the public sector not necessarily seeing more promotions to higher job levels than in the private sector, but in light of having a stronger career start (starting their careers at higher job levels), still holding 'better' jobs on average. Note that this holds even after conditioning on education levels, which is important since the public sector attracts more highly-educated workers.

Next, to study differences in career progression by industry of employment, I restrict to exploring how women and men's life cycle career profiles differ between manufacturing, and education and social services industries. This provides preliminary evidence on heterogeneity in promotion dynamics between industry groups. Workers in the latter industry appear to see more upward movement along the career ladder on average (both men and women), though the gender gap prevails in both. Women in manufacturing seemingly experience very low career ladder progression, but this may partly be explained by shares of women in manufacturing declining between ages 25-30 and 30-35.

Having looked at how certain individual, job-related and family-related characteristics associate with the career dynamics of women and men, in the final part of my analysis I attempt to quantify the contribution of these factors in accounting for the gender gap in average job-level, using a standard Oaxaca-Blinder decomposition approach. This decomposition is carried out at different age windows, allowing us to trace the evolution of this gender gap over the life cycle, as well as that of its unexplained and explained components. I find evidence of a gap in mean job level that cannot be accounted for by the aforementioned characteristics, which comes up around age 30-35 and persists over the remainder of the career life cycle. This is noteworthy in light of the fact that I account for the presence of children. But note that dynamic effects of childbirth are not captured in the decomposition analysis, hence that may account for at least some fraction of the unexplained gap.

Two facts of note about this study are that firstly, the definition of *promotion* (*demotion*)

used is precise. In our data a promotion (demotion) necessarily constitutes a change in job assignment, representing a move along the internal career ladder[2]. This is in contrast to other studies such as Bronson and Thoursie (2018). Each of the five *job levels* constitute tasks with varying levels of autonomy and complexity. Second, the empirical literature on gender career dynamics gap typically focuses only on promotion rates; although to provide a complete picture of career advancement over the life cycle, demotion rates are likely also of importance. This paper, thus, focuses on net career advancement of workers. Though, as documented in Gibbons and Waldman (1999), demotions are a rare occurrence, our data suggests that demotions appear to take some prominence towards the very end of the career life cycle, both for women and men.

In essence, this paper is a study on heterogeneity in career dynamics of women and men, in the German context. It builds on other studies on life cycle wage dynamics heterogeneity in the German context, such as Bayer and Kuhn (2020), as well as on the vast economics literature on gender wage inequality in general (Goldin (2014), Bertrand (2011)). This paper also closely relates to the gender promotion gap literature. As alluded to above, the gender promotion gap literature is marked by heterogeneity in findings. Blau and DeVaro (2007) provide an excellent review and point out that certain papers find a positive gender promotion gap, others negative, and still others find no significant differences at all. This may partly be attributed to differing definitions of promotions used. This thesis seeks to contribute to this unsettled literature. In addition, this paper also connects to the literature on part-time penalty on labor market outcomes (Schrenker (2020)), on child penalties (Kleven et al. (2019)), on public-private sector differentials (Dustmann and Van Soest (1997)), and on decompositions of gender gaps in labor market outcomes (Blau and Kahn (2017), Fortin et al. (2011), Fortin et al. (2017), Bronson and Thoursie (2018)).

Throughout this paper, my analysis and results indicate correlational associations between the variables of interest, not causal relationships. The aim is to provide new evidence, utilizing the strengths of rich survey (panel) data, on gender differences in the association between career progression and individual characteristics, and to quantify how far these factors can go in accounting for said differences.

The rest of the paper is organized as follows. Section 2 introduces the data, and provides summary statistics and descriptions of variables of interest. Section 3 documents gender differences in career dynamics and presents conditional estimates of the potential role of individual characteristics in explaining these gender differences. Section 4 presents the decomposition results for the gender gap in average job level at different stages of the life cycle. Section 5 concludes. References and an appendix follow.

[2]Given the absence of firm-level information in the survey data, one cannot rule out that some of the observed movements along the career ladder may be associated with firm changes. For instance, when a worker at job level 3 wishes to move up the career ladder, but jobs with a higher job-level are not available at her current firm.

2 The German Socio-Economic Panel (SOEP) data

This study uses the German Socio-Economic Panel data (Schupp et al. (2017)). It is a representative longitudinal survey on private households in Germany. It started in 1984, and since 1990 additionally includes a sample from erstwhile East Germany. This paper uses data from all available survey years: 1984-2015.

This data set provides three benefits - an opportunity to directly observe and measure career ladder progression, being a rich source of information on numerous relevant background characteristics of individuals typically not found in administrative data, and providing a panel dimension. The first distinguishes our study in that we do not have to infer promotions/demotions from observed large wage changes, which could also be driven by other non-promotion related reasons. The second allows us to also account for the effects of relevant individual characteristics, job-related characteristics and family circumstances in our study. These include demographic variables such as year of birth, education levels, work experience in both full-time as well as part-time, detailed information on industrial sector and occupation, age, presence and number of children, marital status, and public or private sector employment. Third, the panel dimension of the data allows us to accumulate promotions and demotions at the individual level. Following Bayer and Kuhn (2020), I generate a measure of cumulative net promotions by summing over all promotions up to each age and subtracting all demotions.

Using survey data for life cycle analysis has some drawbacks. One concern is changes in composition of workers over the life cycle. Ideally we would observe all workers for around 30 years, that is from ages 25 to 55. While we observe more than 80% of individuals for large portions of their life cycle (at least 17 years), most of them are not observed for all of 30 years. To reduce concerns of composition changes, in the decomposition analysis of section 4 where the focus is on tracing how the gender gap evolves over the life cycle, I restrict the analysis to ages 25 to 45.

The data does not provide firm-level information. To reduce concerns regarding women systematically sorting into firms which have lower promotion rates (and that driving the gender gap) I control for broad industry groups in my analysis (Appendix A provides details on the aggregation).

The majority of the analysis in this paper is based on private-sector employees aged 25 to 55, with employer size 10 or larger, and excluding self-employed individuals. This holds throughout (including the descriptive statistics presented in Table 1), except for the analysis on public-private sector differences and industries (sections 3.4 and 3.5).

Table 1 provides descriptive statistics for the population of workers in this study. Trends in *job levels* and *cumulative net promotions* are discussed below in section 2.1.

Information on the ISCED-1997 educational classification (provided in the SOEP) is aggregated into three groups as shown in Table 1. 'Low' education refers to general elementary education or less. 'Intermediate' education refers to vocational education and/or *Abitur*, and 'high education' consists of those with higher education. The largest

Table 1. Descriptive Statistics

	Men (Individual-Years)	Women (Individual-Years)
Mean Job Level:		
Ages 25-30	2.40	2.52
Ages 30-35	2.68	2.57
Ages 35-40	2.73	2.46
Ages 40-45	2.70	2.37
Ages 45-55	2.65	2.30
Mean Cumulative Net Career Progression:		
Ages 25-30	0.11	0.06
Ages 30-35	0.19	0.05
Ages 35-40	0.15	0.03
Ages 40-45	0.12	0.03
Educational Attainment and Job Characteristics:		
Share of Low Education	0.09	0.15
Share of Intermediate Education	0.63	0.66
Share of High Education	0.28	0.18
Share Employed Part-Time	0.02	0.42
Marital Status and Children:		
Married	0.68	0.64
Has at least one child	0.62	0.74
Total Individual-Year Observations	69,395	53,249
Total Individuals	11,236	11,396

share of individuals working in the private sector have an intermediate level of education, for both women and men. In our sample women appear to be less educated than men; they are slightly over-represented in the low education group and 18% have a higher education degree, relative to 28% of men. A large share of women (42%) are engaged in part-time or marginal employment, relative to a mere 2% of men (in individual-year terms).

Married is a binary indicator, and includes those in registered same-sex unions. Non-married includes single and divorced individuals.

2.1 Job Levels and Cumulative Net Promotions

The definition of *job levels* used here follows from Bayer and Kuhn (2020), who rely on a different data source (Structure of Earnings Survey) that allows for directly observing job levels of individuals. The SOEP data provides a proxy, and they document that this proxy variable behaves very similarly to the (actual) job level variable of the SES data, though it is inspired from the sociological literature and coded differently. One difference to note is that in the SOEP data, there is lower mobility between job levels. This is reflected in the

average job levels at different age groups (Table 1). This paper utilizes this proxy variable, and from here on, it is always referred to as *job level*.[3]

The *job level* of a worker is tied to the job an individual holds during a given year. Job levels go from 1 to 5, signifying *untrained* workers (UT), *trained* workers (TR), *assistants* (AS), *professionals* (PR) and *management* (MA). This concept enriches the task-based approach of wage determination (Autor et al. (2003)), by adding a dimension of *how* tasks are done, going beyond *which* tasks are done. Movement from a lower to a higher job level is coded as a promotion, and movement to a lower job level is coded as a demotion. Note that this variable has been recoded to correct for spurious transitions over the life cycle of individuals. Survey data is known to be prone to measurement error, which may explain highly-unlikely life cycle patterns in job level; for example, 2-2-4-2 in the span of 4 consecutive years.

Cumulative (net) career progression of an individual records the cumulative number of net promotions seen by a worker at each stage of the life cycle, starting from age 25. It is defined at the individual level for each age as the difference between cumulative promotions and demotions seen by the individual till that age. Thus, it gives us a measure of cumulative progression or *movement* along the career ladder, whereas the job level represents the *level* at which a worker stands on the career ladder. Zero signifies no net progression, positive values mean a worker (in a given year) has seen more promotions than demotions (or zero demotions) till that age, and negative values represent an individual seeing more demotions than promotions till a given year, starting from age 25. In the data it ranges from -4 to +4. +1 signifies a net movement of one job level up, that is, a promotion. Means of this variable over age windows (Table 1) show that we observe very low levels of net career growth. This is linked to the low worker mobility along the career ladder, observed in the data. This holds for men and women, and is even more apparent in women's case. Nevertheless, the focus of this paper is on gender differences, and looking at the career progression of men and women relatively is informative.

In the first panel of Table 1 on average job levels, we note an increasing trend for men over the life cycle, starting at 2.4 and stabilizing around 2.7 by age 45. The data suggests that demotions take some prominence in the late stages of the career life cycle, resulting in a lower mean job level than at age 45 (and consequently, lower cumulative career growth). This pattern holds more strongly for men than for women.

Interestingly, women on average start out at a job level 0.12 higher than men during the first stage of their careers. Despite starting at a slightly higher 'rung' of the career ladder, this advantage is soon lost - in the next stage of their careers (ages 30-35) they are at a lower mean job level than men and remain so persistently over the rest of the life cycle. After age 30-35 there is no further growth - women's mean job levels see a slight decrease and stabilize more or less at the 2.3-2.4 mark till the final stage of the life cycle.

For cumulative career progression, we note that there is a consistent level difference

[3]Starting from survey year 2017, SOEP discontinued providing data on the *job level* proxy variable. Therefore the analysis in this paper is based on years 1984-2015.

in the amount of net upward movement recorded in women's career dynamics relative to those of men. Between ages 25-30, men's net career progression is almost double that of women's, and by the age 40-45 it is, strikingly, four times as high. Women's careers show the highest cumulative growth (net movement of around +0.06 steps) in the first stage of the life cycle, decreasing very slightly in the next stage. Around age 35 there is a decrease in net career progression (possibly brought about by women switching to part-time or marginal jobs associated with lower job levels), and this remains stable till the end of career life cycle - signifying no further promotions or demotions. Both men and women experience the highest career growth in the first half of their careers.

Throughout this paper, I use the terms *cumulative net promotions*, *cumulative career progression*, and *cumulative career growth* interchangeably.

3 Gender Differences in Career Progression over the Life Cycle

In this chapter, I first document the (unconditional and conditional) gender gap in cumulative net career progression. In subsequent sections I present a deeper look into possible factors that could play a role in women and men's career dynamics - working full or part-time, presence of children, marital status, public-private sector differences, and industry of employment. In studying these factors, I draw inspiration from the vast literature in economics on the gender pay gap in developed countries. For each case, I begin by studying the unconditional gender gap using life cycle career profiles for women and men, and further attempt to provide conditional estimates of how they associate with women and men's career dynamics.

Figure 1. Life Cycle Cumulative Net Promotion Profiles, Men and Women

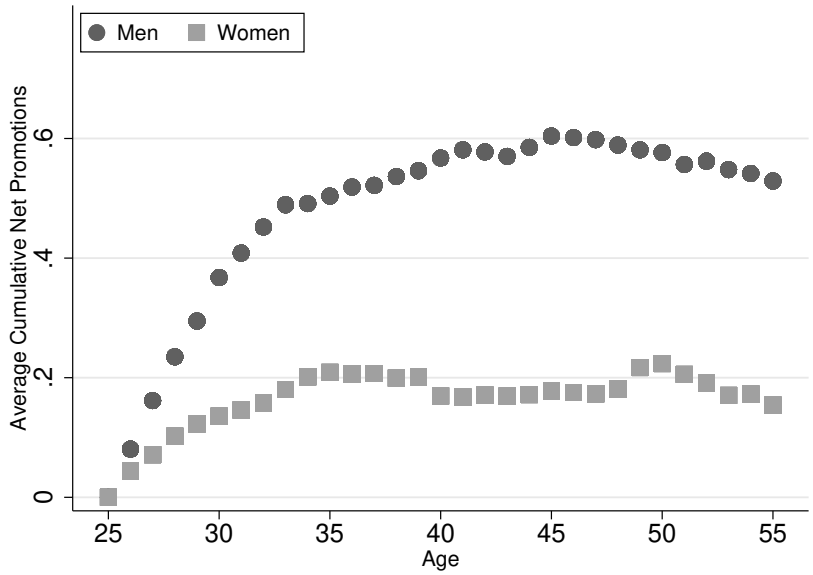


Figure 1 displays average net career progression profiles of all men and women over the

life cycle (working in the private sector), with the accumulated net promotions of workers at age 25 normalized to zero.

This figure summarizes the life cycle career dynamics of women and men, using all information available from survey years 1984-2015 (therefore, birth cohorts are accounted for in generating these profiles). First we accumulate promotions and demotions at the individual level, and (for each gender separately) regress both on a full set of age dummies. Subtracting the predicted cumulative demotions from the cumulative promotions at each age provides us the measure shown in the vertical axis. On the vertical axis, 0.5 signifies half of all workers (within the group of males or females) moved one job level up.

We note large differences in life cycle net promotion dynamics between men and women that come up from the very start of their careers at age 25. Both women and men see the highest career growth in the first half of their careers, though for men the slope is more positive. Men see a slowdown in progression around age 40, while women appear to experience the slowdown earlier around age 35. Towards the end of the life cycle after age 50, we see some evidence of demotions possibly coming into play and lowering cumulative career progress.

Please note that in the average life cycle figure above (and similar figures in subsequent sections), the variable on the vertical axis is constructed by subtracting predicted accumulated promotions and predicted accumulated demotions, and then it is normalized as described above. Hence, the levels shown on the vertical axis do not directly compare to the levels of the *cumulative net promotions* variable that is used as my dependent variable in my regression estimates and which is described in section 2.1 and in Table 1. *Cumulative net promotions* is generated directly - sum over all promotions and demotions at each age for every individual in the panel data, and compute the difference to get the cumulative net promotions (or career progression) for each individual at each age.

The life cycle gender differences observed in Figure 1 could be influenced by underlying systematic differences between women and men, at least in part. Summary statistics presented in Table 1 underscore appreciable gender differences in shares working part-time, and in shares of individuals with high and low education levels. In addition, systematic differences in sorting into certain types of firms, or into certain types of occupations may also play a role. To this end, I attempt to provide a conditional estimate of the gender gap in cumulative net career progression next.

I estimate the following empirical model and report the coefficient on *female* to isolate the conditional gender gap in accumulated net promotions. The dependent variable y_{it} is (cumulative) net career progression of individual i at year t:

$$y_{it} = \alpha + \beta \cdot female_i + \theta X_{it} + \pi_t + \epsilon_{it} \tag{1}$$

where β is the coefficient of interest, X_{it} is the vector of control variables and π_t adds survey year fixed effects. In the first specification, X_{it} represents baseline controls,

and specification 2 adds broad controls. A third specification relates to the analysis on part-time and full-time differences, and its implications are discussed in section 3.1. All baseline and broad controls used in my analysis are described below.

Baseline controls include education level dummies (low, intermediate and high education, as described in Table 1) and years of work experience, to account for differences in human capital levels between women and men. For years of previous work experience, both full-time and part-time are included. Accounting for work experience in part-time may be important since there may be differing returns to experience in full-time and part-time. As discussed in Blundell et al. (2016), returns to part-time experience are worth only a fraction of those from full-time. Working part-time typically leads to small or no improvements in human capital, and in some cases may even be associated with a reduction in human capital accumulation. In addition, a full set of age dummies (to control for underlying life cycle trends), year fixed effects (to control for time trends, business cycles for example), controls for birth cohorts, and an indicator for marital status are included.

Broad controls account for segmentation or sorting into firms (proxied by industry group) and into occupations. There may be systematic differences in these aspects, with women self-sorting into firms with lower promotion rates and/or working primarily in occupations associated with low career progression. Absent firm-level data, I utilize four broad industry groups (details on aggregation of industry information are described in Appendix A), and the ISCO-88 occupational classification (1-digit level) as controls. In addition, I account for the presence of children. To summarize, our conditional estimates in Table 2 present the gender gap in (cumulative) net career growth holding constant each of these factors.

Table 2 presents conditional estimates of the gender gap. Addition of broad controls does not affect the gap recorded in column 1, even appearing to very slightly increase it. The results suggest that conditioning on background characteristics, women on average see 0.07 lower cumulative net promotions than men over the life cycle or, that they climb 0.07 steps (on net) less on the career ladder than men. To put it into perspective, that implies that over the life cycle women experience 58% lower cumulative net career growth than men (the average cumulative career growth seen by men is around 0.12).

3.1 Full-time and Part-time work

I first look into the gender gap between full-time workers and provide evidence that though higher share of part-time work amongst women (in our data, 42% of women are engaged in part-time work, relative to a mere 2% of men) appears to account for a part of the overall gender gap, a significant gap persists even between full-time workers. Next, I focus on within-group differences in women.

Schrenker (2020) provides an excellent overview of the literature on part-time wage differentials (especially in the German context), and discusses that two aspects are important to note when studying part-time work and labor market outcomes. First,

Table 2. Regression Estimates of Gender Difference in Cumulative Net Promotions

	(1)	(2)	(3)
Female	-0.0776***	-0.0784***	-0.0428**
	(0.0147)	(0.0164)	(0.0187)
Basic controls	Yes	Yes	Yes
Broad controls	No	Yes	Yes
Full-time workers only	No	No	Yes
N	122,717	122,717	84,664

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions are based on SOEP waves 1984-2015. Sample includes dependent private-sector employees aged 25 to 55 with employer size 10 or larger. Basic controls (column 1) include educational level indicator (ISCED 1997 classification), years of work experience (both in full-time and part-time), as well as indicators for age, marital status, survey year and birth cohort. Broad controls (column 2) add dummies for major occupational group (1-digit ISCO-88 classification), broad industry group (see details in Appendix A), and for presence of children. Column 3 restricts the sample to only include individuals who worked full-time throughout their observation period.

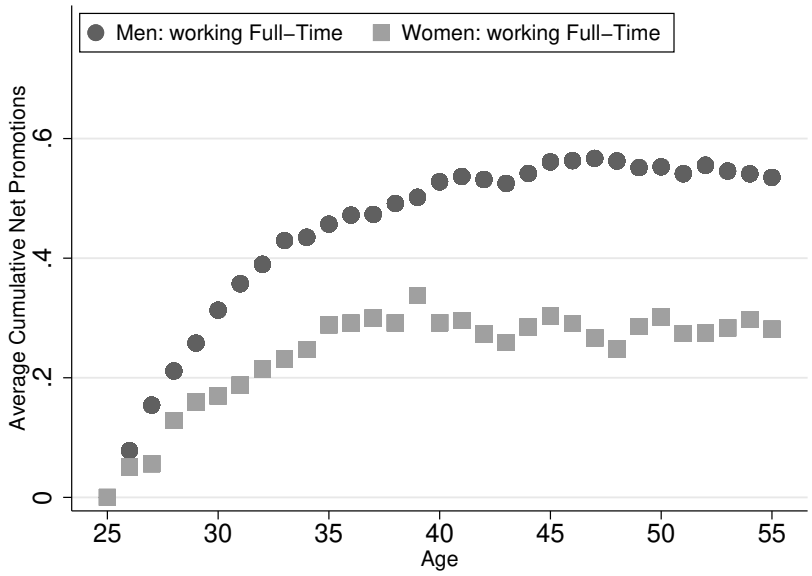
whether marginal employment contracts (for example, 'mini-jobs' which are tax-exempt jobs with maximal monthly earnings of around 450 Euros) are included in the definition of part-time status, and second, whether men are included in the sample of study. I note here that in defining part-time work, marginal jobs are included in my analysis. Second, given the very small share of men with part-time status in our data, I refrain from studying how part-time work may affect men's career dynamics.

3.1.1 Gender Differences among Full-Time Workers

Figure 2 compares the life cycle net career progression profiles (normalized to start from zero at age 25), with the sample restricted so as to only include men and women who worked full-time throughout their life cycle. The individuals in this restricted sample never switched to part-time work during their careers (and likely includes many women without children). We note that compared to the baseline figure (Figure 1) women's career dynamics show greater progression over the life cycle, and as a result the gender gap is lower at all stages of the life cycle. For men, career dynamics look almost identical to the baseline figure, which is unsurprising given the low prevalence of part-time work in this group.

In addition, the third column of Table 2 looks at the conditional gender gap in cumulative net promotions, with the same sample as described for Figure 2. Considering only full-time workers reduces the magnitude to 0.04 (from 0.07 in column 1, showing a decrease of around 40% in the coefficient). But the gender gap persists and remains

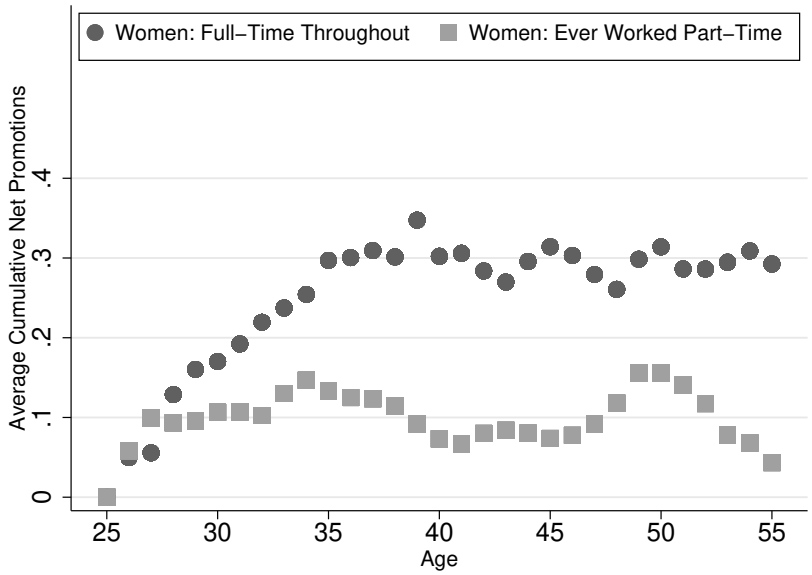
Figure 2. Lifecycle Cumulative Net Promotion Profiles: Full-time workers, Men and Women



significant, implying that full-time female workers climb 0.04 net steps less on the career ladder on average than their male counterparts, over the life cycle. The result implies that a full-time female worker (who does not switch to part-time work ever) will see 33% lower cumulative net progression over the life cycle, at 0.08, than her male counterpart with identical characteristics (men see net career growth of 0.12 on average over the life cycle).

3.1.2 Within-Group Differences for Women

Figure 3. Women's Lifecycle Cumulative Net Promotion Profiles: Working full-time throughout and Ever Worked part-time



Looking at within-women differences, I first present the life cycle career profiles for

two groups of women - those who worked full-time throughout the career life cycle, and those who worked part-time at least at some point during their careers. Within the second group there are mainly two types of female career profiles - those who worked part-time all through their careers, and those who switched between full-time and part-time work over their career life cycles.

Figure 3 points towards part-time work likely being negatively associated with women's (net) career progression profiles. For women who ever worked part-time we see strong growth in their career dynamics till age 27, after which there is a slowdown in progression for the next 5-6 years. One plausible explanation that may be driving this trend is that women switch from full to part-time (or marginal) jobs in and around that age. This gap between the two female groups widens and persists till age 50. This motivates the next part of my analysis - to estimate the penalty of working part-time on cumulative net career progression (y_{it} for female i at year t) whilst conditioning on possible confounding variables, for which I look at the following model:

$$y_{it} = \alpha + \beta \cdot \mathbb{1}\{j_{it} = PT\} + \theta X_{it} + \gamma_i + \pi_t + \epsilon_{it} \tag{2}$$

where $j_{it} \in \{FT, PT\}$, β is the coefficient of interest, X_{it} is the vector of control variables, γ_i an individual-specific fixed effect, and π_t adds survey year fixed effects. Controls used are listed under Table 3, and follow those used for equation (1). Please see the explanation below equation (1) for details on baseline and broad controls used.

Table 3. Estimates of Part-Time Penalty on Cumulative Net Promotions, for Women

	Women (1)	Women (2)	Women (3)
Working Part-Time	-0.111***	-0.0922***	-0.0887***
(indicator)	(0.0159)	(0.0158)	(0.0166)
Basic controls	Yes	Yes	Yes
Broad controls	No	Yes	Yes
Individual FE	No	No	Yes
N	53,215	53,215	53,215

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions are based on SOEP waves 1984-2015. Sample includes female dependent private-sector employees aged 25 to 55 with employer size 10 or larger. Basic controls (column 1) include educational level indicator (ISCED 1997 classification), years of work experience (both in full-time and part-time), as well as indicators for age, marital status, survey year and birth cohort. Broad controls (column 2) add dummies for major occupational group (1-digit ISCO-88 classification), broad industry group (see details in Appendix A), and for presence of children. Column 3 adds individual fixed effects.

In Table 3, column 1 (pooled regression with controls for human capital attainment, life cycle trends, time trends, birth cohort and marital status) shows that on average, women working part-time climb 0.1 steps less on the career ladder on net than those working full-time. Column 2, which additionally takes into account industrial and occupational sorting, and presence of children, suggests they climb on average 0.09 steps less on net. Column 3, where identification comes from within-worker switching between full and part-time employment suggests that on average a woman changing to part-time work will see her net career progression fall by 0.08. These estimates reflect a strikingly strong penalty since in our data the mean cumulative (net) career growth of full-time female workers is 0.07. This suggests that switching to part-time work may lead to a negative level of cumulative net promotions, which is not impossible (recall that our dependent variable goes from -4 to +4, negative values indicating a worker sees more demotions than promotions till that age.)

I qualify the magnitude of the effect by noting that it is likely driven by inclusion of marginal employment contracts into part-time status. The *job level* variable of SOEP data is a proxy designed to reflect an 'occupational prestige' scale inspired from the sociological literature. It is strongly plausible that marginal contracts are not associated with high social prestige, perhaps all being assigned to the lowest job level. Indeed, in our data more than 60% of part-time jobs have a job level of 1 or 2, with a large majority of the rest of part-time jobs being at level 3. Women switching from a full-time job to a mini-job will see a sharp fall in their job level. Another caveat is that this analysis does not account for worker selection into part-time, which may further inflate the magnitude of the penalty observed.

The key takeaway from the analysis is that part-time work is indeed associated with lower career growth for women. It does not however fully explain the observed gender heterogeneity in career dynamics.

3.2 Motherhood and Fatherhood

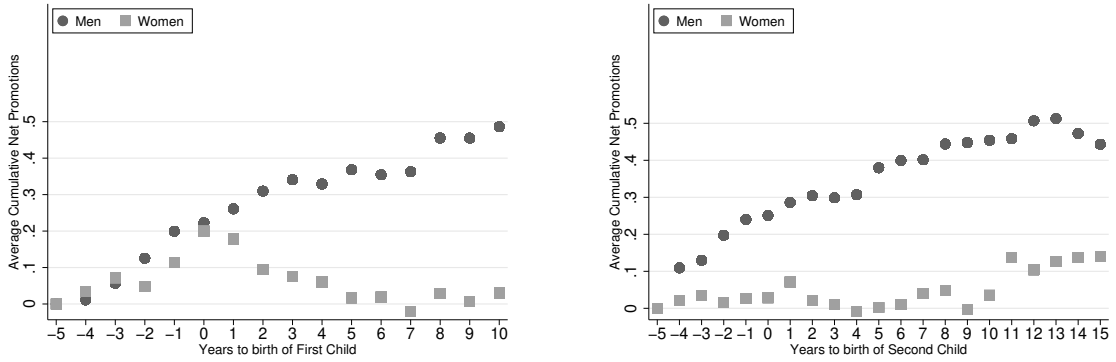
To examine the heterogeneous effects of children on workers' career dynamics, I first visualize cumulative career progression for men and women before and after the birth of their first and second children, with some inspiration from the event-study analysis by Kleven et al. (2019) on the effect of childbirth on wages. Next, I look into within-men and within-women differences in net promotions over the life cycle by presence of children, first generating life cycle career profiles for each group and second, providing estimates of the gap conditional on various characteristics.

3.2.1 The Event of Childbirth

In Figure 4, I zoom in on the years before and after childbirth and visualize the promotion dynamics for men and women during that time period. I focus on the events of first and second child-birth. I follow Kleven et al. in looking at five years before and ten years

after first childbirth. In these promotion profiles, the coefficients simply correspond to the mean values of the outcome for each relative to year of childbirth. These figures do not represent causal evidence, since here we do not control for underlying life cycle or time trends. The clear trends we observe however point towards dynamic effects of childbirth having a significant effect on net promotion dynamics of women.

Strikingly, for the event of first childbirth, the generated figure presents some very clear patterns - women's career progression, which had been on an upward trajectory during the years before childbirth, begins to stall starting from the year after childbirth and this negative effect appears to persist over the subsequent years, up to a decade after the birth of first child. For men, career progression displays an upward trend during this entire time frame, and the event of childbirth appears to have no effect.



(a) Years Relative to First Birth **(b)** Years Relative to Second Birth

Figure 4. Career Progression, by Years Relative to First and Second Birth

Figure 4(b) presents the same figure, with the event of interest here being the birth of the second child (represented by year 0). For women, as one would expect, we do not see positive career progression before year 0, as we do in Figure 4(a), since these were the years in the immediate aftermath of the birth of the first child. Between five years before and ten years after the birth of the second child, career dynamics of women remain stably at a low level, displaying little positive growth. Men display positive net promotion dynamics in totality, throughout the time frame. There are periods of net positive career progression (promotions) interspersed with periods of zero net career progression (neither promotion nor demotion). Around ten years after the event, we begin to see signs of women's careers progressing again.

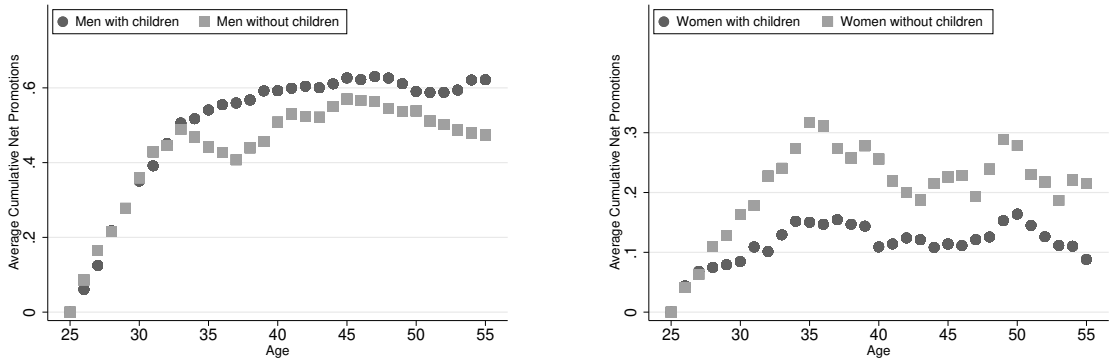
These figures, though not representing conclusive causal evidence, present strong evidence for dynamic effects of childbirth having an immediate and persistent effect on the career dynamics of women. Similar results are reported in Bronson and Thoursie (2018).

3.2.2 Presence of Children and Career Dynamics by Gender

In the second part of the analysis, I focus on within-gender differences in net promotion dynamics by presence of children. I divide the sample by gender into individuals with and

without children, and compare the generated average life cycle career progression profiles for the two groups. This is done separately for men and women.

From Figure 5, it immediately stands out that within each panel, a level difference in net career progression is visible. For men (first panel), the career dynamics gap is in favor of those with children, but for women (second panel), it is in favor of those without.



(a) Men with and without children

(b) Women with and without children

Figure 5. Evidence for Fatherhood Premium and Motherhood Penalty on Career Progression (Relative to men and women Without Children)

Over almost the entire life cycle, women without children appear to consistently experience better career progression than women who have children. We also observe that women without children appear to have more ups and downs in their net promotion dynamics but the main takeaway from this figure is the consistent level difference between the two within-female groups.

For men, we observe that career dynamics of those without children appear to very closely track that of men with children till around age 32-33. Starting around that age, the second group starts to experience a slowdown in career progression, though in a few years it picks up again and by age 45 men without children are almost at par with those without.

The figures discussed above present a picture of the unconditional gap between within-gender groups, in cumulative career progression. Next I look into the possibility of an association between presence of children and one's job level, for both genders. I focus on the first twenty years of the career life cycle, which is when vast majority of people have small children to take care of.

The model with dependent variable *job level* of individual i at year t, is as follows:

$$y_{it} = \alpha + \beta \cdot \mathbb{1}\{j_{it} = child\,present\} + \theta X_{it} + \pi_t + \epsilon_{it} \tag{3}$$

where $j_{it} \in \{at\,least\,1\,child\,present,\ no\,child\}$, β is the coefficient of interest, X_{it} is the vector of control variables, and π_t includes year fixed effects. Controls used are listed under Table 4. Detailed explanations of controls employed are provided in section 3.1.

Here our outcome variable of interest is the *job level*. Given the ordered and discrete nature of the dependent variable (ranging from 1 to 5), estimates from ordinary least-squares linear regression may not be appropriate. In Appendix 2, I present estimates from an ordered probit regression on the same model as a robustness check. Keeping with the rest of the analysis in this paper and in the interest of direct interpretability, I present ordinary least squares estimates in Table 4.

Table 4. Average Job Level and Presence of Children, estimated separately for Women and Men, Ages 25-45.

Dep. Variable: Job Level	Women (1)	Women (2)	Men (1)	Men (2)
Have at least one child (indicator)	-0.138***	-0.0572***	0.0415	0.0777***
	(0.0372)	(0.0241)	(0.0343)	(0.0240)
Basic controls	Yes	Yes	Yes	Yes
Broad controls	No	Yes	No	Yes
R-squared	0.308	0.585	0.600	0.602
N	37,474	37,474	48,589	48,589

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions are based on SOEP waves 1984-2015. Sample includes dependent private-sector employees aged 25 to 45 with employer size 10 or larger. Basic controls (Women (1) and Men (1) columns) include educational level indicator (ISCED 1997 classification), years of work experience (both in full-time and part-time), as well as indicators for age, marital status, survey year and birth cohort. Broad controls (columns 2) add dummies for major occupational group (1-digit ISCO-88 classification) and broad industry group (see details in Appendix A).

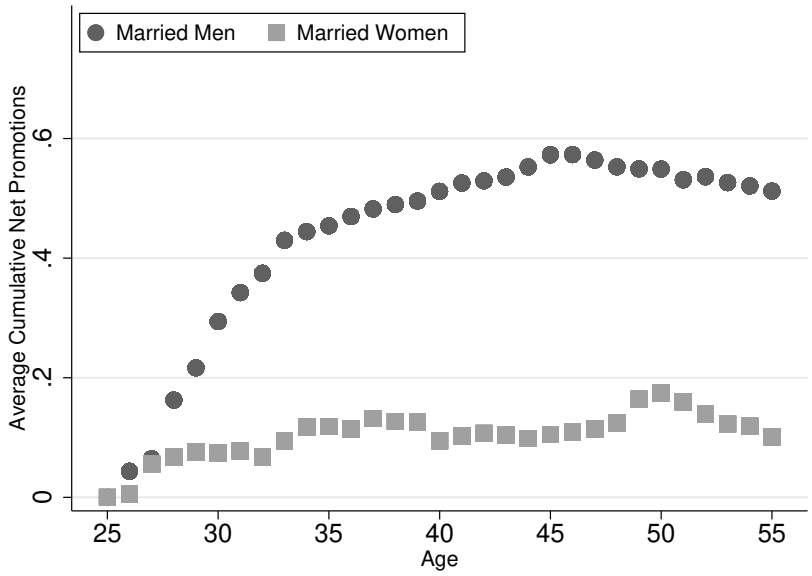
Though insufficient for making causal claims, I note that after conditioning on a broad set of controls (industrial and occupational sorting, in addition to the basic human capital controls), we find that between the start of one's career and age 45, having children is associated positively with men's average job levels, and negatively for women's. For women, having children may be associated with being 0.06 steps below the career ladder on average, relative to those without kids. For men, it is associated with being 0.07 steps above the ladder relative to those without kids on average. Though in our data the career ladder goes from 1 to 5 in principle, but descriptive statistics presented in Table 1 point towards low mobility between levels. For men it ranges from 2.4 at age 25-30 to 2.7 at age 40-45. With that in mind, the magnitudes of the coefficients observed here are notable.

While the simple 'human capital' specification for men shows no significant effect, adding controls for industry groups and occupations reveals a significant positive association between having children and one's average job level. Overall, the career dynamics penalty of presence of children on women is evident (relative to women without children). For men, the results are less clear. I cautiously interpret it as preliminary evidence on a fatherhood premium on career dynamics of men (relative to men without children).

3.3 Marital Status

I look into how marital status may relate to life cycle (net) promotion dynamics for women and men. Marital status is a characteristic that changes over the life cycle. In Figure 6, 'married' includes those who were married at least once between ages 25 to 55. This includes individuals who, for example, were single till age 30 and got married at 31, or were married at first and got divorced later in life. I also include individuals in registered same-sex unions in the married sample. Individuals who never got married even once over the life cycle are excluded. Married men (women) constitute 68% (64%) of our sample in individual-years, as mentioned in Table 1.

Figure 6. Lifecycle Cumulative Net Promotion Profiles: Married Men and Women



Comparing Figure 6 to the life cycle career profiles of men and women unconditional on observables (Figure 1), we see that the career dynamics of married men closely tracks that of men from the first figure. Married women however, seem to experience a lower level of career progression (compared to all women, shown in Figure 1) almost throughout the life cycle, starting in the late twenties and persisting till the late forties. These career profiles point towards marital status not having any meaningful effect on the career dynamics of men, whilst perhaps negatively affecting that of women's. This motivates the next steps of the analysis - try to isolate the effect of being married and check if it indeed associates differently with career dynamics of women and men.

I restrict the coding of the *married* variable such that we only observe individuals as married or non-married. Individuals who are married (whether living separately or together) as well as those in registered same-sex unions are counted as *married*. *Non-married* is defined as being single or being divorced.

The model with dependent variable *cumulative net promotions* of individual i at year t, is as follows:

$$y_{it} = \alpha + \beta \cdot \mathbb{1}\{j_{it} = married\} + \theta X_{it} + \gamma_i + \pi_t + \epsilon_{it} \quad (4)$$

where $j_{it} \in \{married,\ non-married\}$, β is the coefficient on the indicator for *married*, X_{it} is the vector of control variables, γ_i an individual-specific fixed effect, and π_t includes year fixed effects.

Table 5. Cumulative Net Career Progression by Marital Status, estimated separately for Women and Men

	Women(1)	Women(2)	Women(3)	Men(1)	Men(2)	Men(3)
Married	-0.0564***	-0.0392*	-0.0437*	0.00247	-0.0116	0.0316
	(0.0209)	(0.0220)	(0.0261)	(0.0227)	(0.0232)	(0.0221)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Broad controls	No	Yes	No	No	Yes	No
Individual FE	No	No	Yes	No	No	Yes
N	53,303	53,303	53,303	69,414	69,414	69,414

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions are based on SOEP waves 1984-2015. Sample includes all dependent private-sector employees aged 25 to 55 with employer size 10 or larger. Basic controls (Women (1) and Men (1) columns) include educational level indicator (ISCED 1997 classification), years of work experience (both in full-time and part-time), as well as indicators for age, survey year and birth cohort. Broad controls (columns 2) add dummies for major occupational group (1-digit ISCO-88 classification), broad industry group (see details in Appendix A), and for presence of children. Columns 3 include individual fixed effects.

Looking at the results for women in Table 5, column 1 (basic controls) shows a strongly significant negative association of being married on women's cumulative net career progression. However, perhaps unsurprisingly, controlling for industrial and occupational segmentation, and for the presence of children greatly reduces the significance of the result (column 2) and also the magnitude.

One explanation for this is likely the prevalence of societal and institutional norms in Germany that have historically incentivized married women towards part-time work (and relatedly, sorting into professions and industries where flexible and part-time hours are common, but promotions may not be). As we noted in section 3.1, there is a part-time career growth penalty for women. Through the joint tax-splitting scheme, married couples in Germany are encouraged to have the secondary earner of the household not work in a full-time capacity, resulting in married women (typically the secondary earner) frequently working part-time or not participating in the labor market at all. In addition, lack of sufficient childcare also hinders their full participation in the labor force, though since 2005 many reforms have been initiated in this regard. Note that this paper uses data going from 1984 to 2015, hence these historical trends will be reflected in our results. Though I control for having part-time history in the regression, married women (especially

those with children) sorting into 'family-friendly' professions that allow for part-time work but have lower scope of promotions and career advancement, likely explain the 'marriage penalty' in career progression of women seen in Table 3.

The last three columns of Table 5 show the results for men. Across all specifications, we find no significant evidence of marital status having an effect on the career dynamics of men. This is in line with what we noted earlier in the career profiles of men (Figure 6).

3.4 Public and Private Sector

Most of the analysis in this paper revolves around the career dynamics of workers in the private sector. In this section (and the next one), I slightly digress and look into the possibility of there being meaningful differences between the private and public sectors in this respect. I present relevant descriptive statistics for the public sector, and compare life cycle net career progression profiles of male and female workers in public and private sectors. Higher share of highly-educated workers in the public sector call for a closer look into career profiles for each education group separately. Finally, I try to isolate the effect of public sector employment on career profiles of women and men, controlling for observables (especially education levels). Results suggest that the public sector may not be characterized by higher promotion rates than the private sector, but I find evidence of a public sector premium on job levels for both women and men. In light of the fact that workers in this sector aged 25-30 are on a higher job level than their private sector counterparts, this points towards public sector employees seeing a stronger career start (they start at a higher 'rung' of the career ladder), and while they may not climb more steps up the ladder over the life cycle than private sector workers, this initial advantage likely sees them reach higher job levels on average over the life cycle.

This section of my study is inspired by and follows from Dustmann and Van Soest (1997), who provide a study of wage structure differences between the two sectors in Germany (also using SOEP data). Akin to their analysis, I include both *Beamte* as well as other public sector workers in defining public sector employees.

Table 6 provides summary statistics for individuals employed in the public sector in our data. On comparing these statistics to those for the private sector sample (Table 1), there emerge a few points to note. First, the public sector attracts a large share of highly educated workers. This is true particularly amongst women. 43% of women working in the public sector are highly educated, compared to a mere 18% in the private sector.

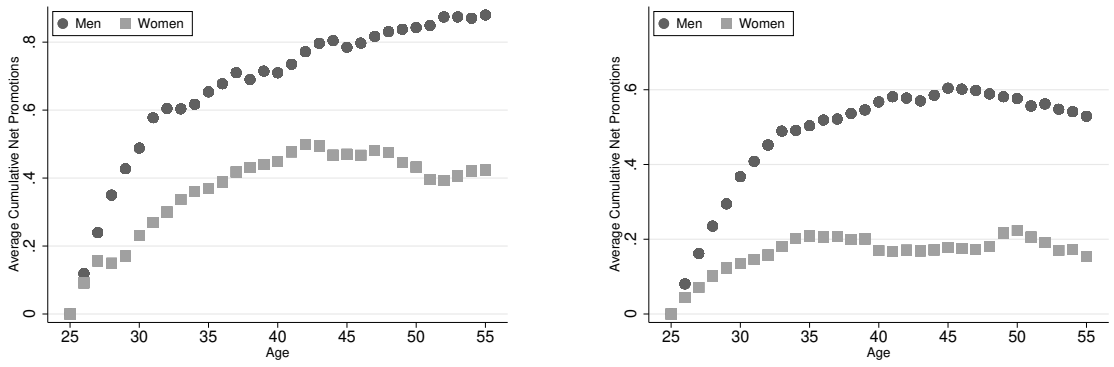
Second, the share of workers with low education levels is lower than in the private sector, for both women and men. Only around 10% of women working in public have a low level of education, compared to 15% in private. Shares of workers (both female and male) with intermediate education are comparable in both sectors.

Finally, Table 6 provides evidence of the public sector providing a stronger career start for employees. This holds for both men and women. Early in their careers, at ages 25-30, male public sector employees are on average at job level 2.90 (2.97 for women), higher than

Table 6. Descriptive Statistics for Public Sector

	Men (Individual-Years)	Women (Individual-Years)
Mean Job Level:		
Ages 25-30	2.90	2.97
Ages 30-35	3.12	3.05
Ages 35-40	3.21	3.00
Ages 40-45	3.25	2.95
Ages 45-55	3.24	2.82
Educational Attainment:		
Share of Low Education	0.05	0.09
Share of Intermediate Education	0.53	0.48
Share of High Education	0.42	0.43
Total Individual-Year Observations	24,290	32,059

the private sector average of 2.40 (2.52 for women). The initial advantage that women held in terms of being at a higher job level at ages 25-30 is observed in both the sectors. Over the entire life cycle, average job levels in the public sector consistently stay at a level above those in the private sector, for both genders.



(a) Public Sector **(b)** Private Sector

Figure 7. Lifecycle Career Progression Profiles, Public and Private Sectors

Figure 7 compares average cumulative net promotion profiles (normalized to level zero at age 25 for both genders) in the public and the private sectors. Note the level difference in profiles for each gender between the two sectors. Both men and women appear to progress up the career ladder more than private sector workers. One way to interpret these figures may be that almost 80% of men in the public sector climb up one job level by age 45, relative to around 60% in the private sector. For women, around 50% climb one level up by age 45, relative to only 20% in the private sector.

At least till age 45, the gender gap is consistently lower in the public sector. This points towards the public sector perhaps promoting women more, but also note that a very

high share of women with high education work in the public sector, rather than in private.

Profiles for both genders are characterized by stronger upward growth and almost no demotions up to age 45. Demotions are reflected as a fall in the cumulative career profile, as we see for women around age 40 in the private sector. This does not imply that demotions do not happen at all in the public sector, but they appear to be less frequent. This trend is also reflected in mean job levels over different age windows (both women and men), shown in Table 6.

It may be the case that the better career dynamics observed (for both women and men) in the public sector are primarily driven by education level differences. The large share of highly educated individuals (who are likely to see strong career dynamics regardless of sector) may be a potential confounder in this regard. To address this possible issue, I next present career profiles for each educational group, and subsequently present estimates of the public sector premium for women and men whilst conditioning on education levels.

3.4.1 By Education Levels

In generating the predicted life cycle profiles of Figure 8, an issue is the low number of observations, hence these may not be representative of the true population. The only aim here is to glean some patterns from an overall comparison between profiles for different education level groups.

Career profiles by educational levels indicate that indeed at all education levels, the gender gap in the public sector is on average lower than that in the private sector, over the average career life cycle. Although, it should be noted that this is especially prominent in the high education group. This suggests that highly educated women sorting into the public sector does explain away some of the perceived benefits of the public sector for women's career dynamics.

For groups with high and low education levels, career dynamics appear to be very similar for men across sectors. In contrast, for highly educated and low-educated women, being in the public sector provides an advantage in net promotion rates relative to the private sector.

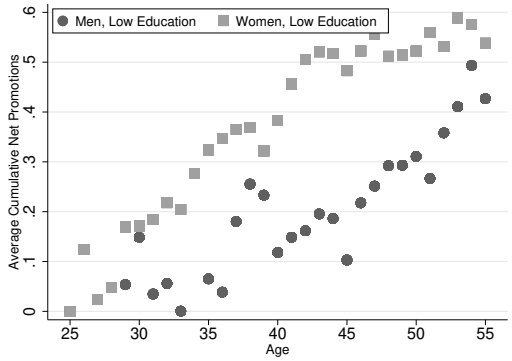
3.4.2 Evidence on Public-Sector Premia on Average Job Level

On looking at the conditional effect of being in the public sector directly on *cumulative net promotions*, we find no significant results. This may appear to suggest that after conditioning on observables (especially education levels) there is no significant effect of public sector employment on career dynamics. However, I posit that this relates to how the *cumulative net career progression* variable is coded and what it seeks to measure, compared to the *job level* variable. This in turn relates to what we observed earlier in Table 6, that public employees start on a higher job level on average.

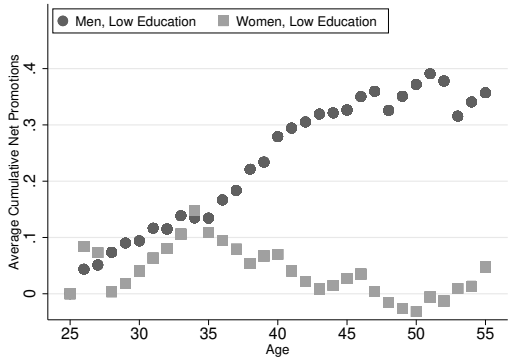
Job levels describe which step of the career ladder a worker is on, whilst cumulative net promotions provide a measure of net *movement* along the career ladder. If a worker

Figure 8. Lifecycle Career Progression Profiles by Education Levels, Public and Private Sectors

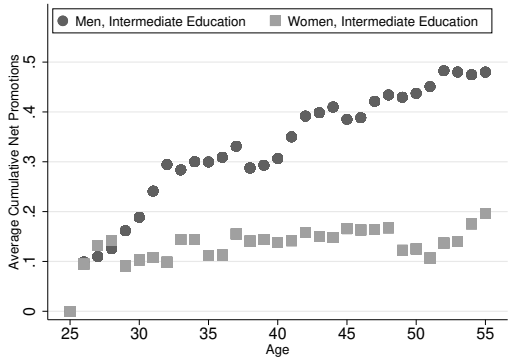
(a) Public Sector: Low Education



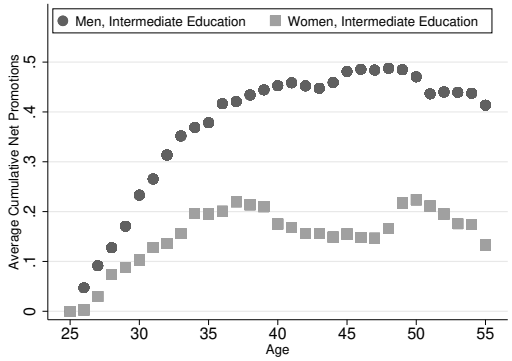
(b) Private Sector: Low Education



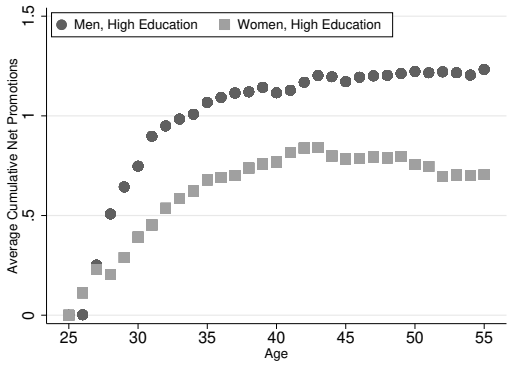
(c) Public Sector: Intermediate Education



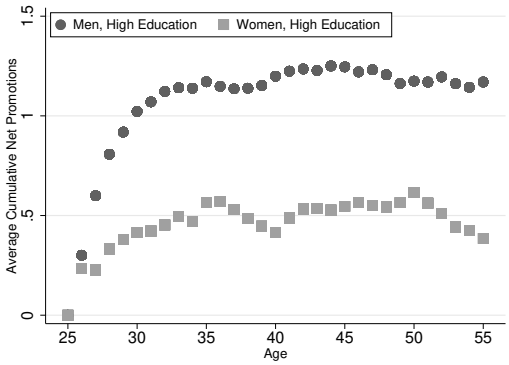
(d) Private Sector: Intermediate Education



(e) Public Sector: High Education



(f) Private Sector: High Education



starts her career at level 3 (as Table 6 shows, many women indeed do), and moves up to level 5 over her career life cycle, her cumulative net promotions will be coded as +2. Another worker starting at level 2 (like many women in the private sector) and ending at level 4 will also have +2 as her cumulative net promotions. This does not capture the important dimension in which the careers of these two workers differ (which step of the ladder they are on), though both see the same amount of net movement.

With this in mind, I examine the effect of working in the public sector for women and men's *job levels*, conditioning on educational levels (along with other observables). The specifications used are inspired from Dustmann and Van Soest (1997), and I additionally

present a specification with individual fixed effects. Given the ordinal nature of the dependent variable, Appendix B provides results of fitting an ordered probit model as a robustness check. I present ordinary linear regression estimates in the main part of the paper to include individual fixed effects specifications, given the panel nature of the data. The model is as follows.

$$y_{it} = \alpha + \beta \cdot \mathbb{1}\{j_{it} = Public\,Sector\} + \theta X_{it} + \gamma_i + \pi_t + \epsilon_{it} \tag{5}$$

where $j_{it} \in \{Public\,Sector,\ Private\,Sector\}$, β is the coefficient on the indicator for *Public Sector*, X_{it} is the vector of control variables, γ_i an individual-specific fixed effect, and π_t includes year fixed effects.

Table 7 presents the conditional estimates of the effect of public sector employment on job levels, for women and men separately. Note that in these regressions I do not control for industry groups, since certain industries are predominantly public-sector oriented and this may control away part of the effect I am trying to capture. The first columns (Women(1) and Men(1)) include basic controls for education levels, age (control for underlying life cycle trends), marital status and survey year (time trends). Broad controls (second columns) add years of work experience (in both part and full-time), indicator for major occupational group, birth cohorts and presence of children. The third removes individual fixed effects.

Table 7. Estimates of Public-Sector Premium on Job Level, estimated separately for Women and Men.

Dep. Variable: Job Level	Women(1)	Women(2)	Women(3)	Men(1)	Men(2)	Men(3)
Public Sector (indicator)	0.239***	0.0336**	0.0430**	0.304***	0.153***	0.00137
	(0.0154)	(0.0149)	(0.0173)	(0.0182)	(0.0196)	(0.0224)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Broad controls	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes
R-squared	0.375	0.620	0.904	0.407	0.610	0.902
N	85,038	85,038	85,038	103,794	90,636	90,636

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions are based on SOEP waves 1984-2015. Sample includes all dependent public and private sector employees aged 25 to 55 with employer size 10 or larger. Basic controls (Women (1) and Men (1) columns) include educational level indicator (ISCED 1997 classification), as well as indicators for age, marital status and survey year. Broad controls (columns (2)) add years of work experience (both in full-time and part-time), indicators for major occupational group (1-digit ISCO-88 classification), birth cohorts and for presence of children. Columns (3) add individual fixed effects.

The results point towards there being a public-sector premium on workers' job levels. The first columns with controls for education levels indicate strong positive associations.

However for both women and men, controlling for occupational sorting reduces the magnitude of the effect. Looking at the second specifications, we find evidence of female workers in the public sector being 0.03 steps (or job levels) higher on average on the career ladder than those in the private sector. For men, the advantage is stronger and they are on average 0.15 steps above. Although the career ladder in our data in principle ranges from 1 to 5, recall that mean job levels over the life cycle range between 2 to 3 in practice. Hence, these effects are noteworthy. Fixed effects estimates (where identification comes from switching between the two sectors) suggest women gain 0.04 steps on the career ladder by switching from private to the public sector. For men, the implication of the third specification is less clear, it may be the case that within-individual switching for men does not provide any benefit, or this may be due to too few men switching between sectors in our data. Switching is indeed more common amongst women, typically after the birth of first child, women may switch to public sector jobs since they are associated with more family-friendly policies, especially in recent years.

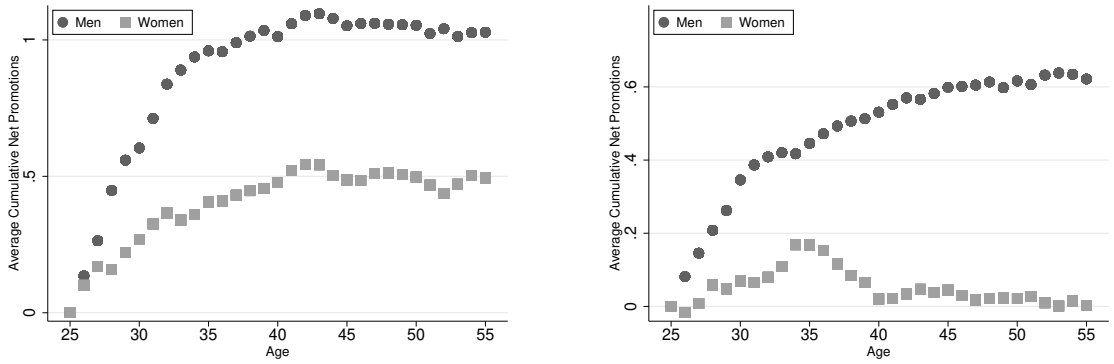
3.5 Industries

In this section I document the prevalence of industry differences in net promotion rates for women and men. I restrict this analysis to presenting preliminary evidence on such differences. It has been established in the empirical literature that for explaining gaps in labor market outcomes, within-firm factors play a greater role than between-firm factors. For instance, Bayer and Kuhn (2020) show the *job component* explains a larger share of life cycle wage dynamics than the *plant component*, for both women and men. Bronson and Thoursie (2018) show a similar result for promotion rates - controlling for firm fixed effects does not decrease the gap in promotions meaningfully.

Nevertheless, differences between firms or industries in their organizational structures may help shed some light on the gender promotions gap. If one industry systematically promotes women less than others, then that may be a starting point for policymakers in addressing the gender career progression gap. Here, I look into two broad industry groups - education and social services , and the manufacturing sector.

One important difference between the two industries not reflected in the life cycle profiles is the shares of women and men. In our data, women constitute around 75% of the workforce in the education industry, and this share remains constant throughout the life cycle. In manufacturing, shares change over the life cycle. Between ages 25-30, women represent 35% of workers in manufacturing, but by age 30-35 the share reduces to around 28% and does not increase much over the next years.

Life cycle career progression profiles for both genders by industry reveal some patterns. First, both men and women in manufacturing see lower net promotions over the life cycle than in education. Second, both display sizable gender gaps over the life cycle which come up in the first half of the working life and persist. But the gap is especially stark in manufacturing. In education, both genders progress up the career ladder, though women



(a) Education and Social Services **(b)** Manufacturing

Figure 9. Lifecycle Career Progression Profiles, by Industry

are consistently a level below men. In contrast, in manufacturing, women appear to see negligible progression, while men's careers progress upwards. The sharp fall in career dynamics of women around age 35 may be explained by many women leaving the industry around that age, since around that time we see their shares declining. This analysis cannot comment on the possible reasons behind these large differences by industry, or on if there are other underlying systematic differences driving these differences. It brings to light some evidence that may be relevant for further research.

4 Decomposition of Gender Gap in Mean Job Level

In Section 3, I first established the existence of a gender gap in career progression, and went on to look at the possible role certain job-related or family-circumstance related factors could play in driving this gap. For instance, the share of women involved in part-time work is far greater then the share of men, and being in part-time work indeed appears to be negatively associated with promotion dynamics over the life cycle. Likewise, the presence of children and one's marital status is also negatively correlated with average job level and net career progression respectively, for women. In this section, I attempt to answer the question - how far do these factors go in explaining the observed differential? Can they collectively account for the entirety of the gap, or does a fraction of the gap continue to exist even after accounting for these differences in characteristics?

Results in Table 2 already provide a hint towards the answer. Even after accounting for a rich set of control variables - education level, work experience in both full- and part-time, marital status, presence of children, broad industry and occupational group, I find evidence in support of the presence of this gap. Restricting the sample to only include men and women who worked full-time throughout the life cycle, reduces the magnitude but does not change this result very meaningfully.

One method to attempt to answer this important question is through carrying out an Oaxaca-Blinder decomposition analysis (Oaxaca (1973), Blinder (1973)). This method

decomposes the gender gap in means of the outcome variable of interest - the average job level, in our case - into an explained and an unexplained component. It is typically employed in the economics literature to decompose the gender gap in wage levels or earnings (for example, see Blau and Kahn (2017), Fortin et al. (2017), Kleven et al. (2019)).

Intuitively, this decomposition analysis predicts counterfactual job-levels for women, in a world where their characteristics would be 'priced' at the same level as that of men. That is, they will see the same returns to characteristics as men. Phrased differently, we ask: what would be the average job level of men if they had the same characteristics as women?

I focus on certain age windows over the life cycle (ages 25-30, 30-35, 35-40 and 40-45), and decompose the gap in average job level for each of these age windows separately. The aim is to track the evolution of the gender gap, as well as the dynamics of the explained and unexplained components of this gap, over the life cycle. In line with most of the analysis conducted in this paper (with the exception of sections 3.4 and 3.5), I restrict my attention to dependent employees aged 25-55 working in the private sector.

4.1 Oaxaca-Blinder Decomposition Method

In line with the traditional Oaxaca-Blinder decomposition literature on wage rate differentials, I employ a two-fold analysis. Fortin et al. (2011) provide a comprehensive overview of this method, detailing its advantages and its limitations.

This decomposes the observed gap (at the mean) in the outcome variable of interest between males and females into two components - an 'explained' component and an 'unexplained' component. The explained component can be accounted for by differences in characteristics, whilst the latter (which represents differences in how the same characteristics of men and women are 'priced' in the labor market) is often taken to represent discrimination in the labor market. It may however be indicative of other characteristics that have not been included into our measured specification, such as gender differences in work effort, competitiveness and so forth.

The following equations present the decomposition, following from those presented in Blau and Kahn (2017). For each of the four age windows studied, I estimate separate regressions for males and females, with *job level* as my dependent variable. Subscript for individual i is omitted.

$$y_m = \alpha + X_m\beta_m + \epsilon_m \tag{6}$$

$$y_f = \alpha + X_f\beta_f + \epsilon_f \tag{7}$$

where for each gender, X is the vector of explanatory characteristics (each of the factors studied in section 3), β is the corresponding vector of coefficients and ϵ is an error term. Let $\widehat{\beta_m}$ and $\widehat{\beta_f}$ be the estimates of β_m and β_f, and $\overline{X_m}$ and $\overline{X_f}$ denote mean values

of characteristics. Then we have:

$$\overline{y_m} - \overline{y_f} = \widehat{\beta_m}\overline{X_m} - \widehat{\beta_f}\overline{X_f} = \widehat{\beta_m}(\overline{X_m} - \overline{X_f}) + \overline{X_f}(\widehat{\beta_m} - \widehat{\beta_f}) \tag{8}$$

$\overline{X_f}(\widehat{\beta_m} - \widehat{\beta_f})$ denotes the impact of gender differences in characteristics evaluated using the male coefficients. $\widehat{\beta_m}(\overline{X_m} - \overline{X_f})$ denotes the unexplained component.

These equations refer to the case of creating a counterfactual where women receive the same returns to characteristics as men. Alternatively, men could be assigned female returns to characteristics, that is, we could instead use female coefficients and the male averages.

For this decomposition, our dependent variable is ordinal. Fairlie (2005) provides a variant of the Oaxaca-Blinder method suited for cases with a binary indicator variable as the outcome. To my knowledge, there is currently no variant that allows for decomposing an ordinal variable (with five levels). This analysis uses classic linear regression.

4.2 Results

Tables 8 and 9 together provide the decomposition results. The first decomposes the mean gap in job levels observed for age windows 25-30 and 30-35. The latter presents the same for ages 35-40 and 45-45. Due to concerns regarding compositional changes, I restrict the focus of this decomposition analysis to the first 20 years over the life cycle.[4]

Traditional O-B decompositions of gender wage gaps typically do not account for children. This analysis, revolving around career dynamics, differs from the traditional implementation of the method in two ways: first, our outcome variable of interest is *job levels*, and second, in addition to the traditional characteristics, I also attempt to account for the contribution of marital status and presence of children in the decomposition (which I combine into the *family component*).

For each age window, I study the contributions characteristics presented in Section 3 in accounting for the mean gap. I present the contributions of four primary components: education component, work experience, job component and family component. *Education* and *work experience* can together be thought of as representing the *human capital component* of the gap. *Job component* comprises of relevant characteristics of an individual's job: whether the job is a regular full-time position or done on a part-time basis (regular part-time employment or marginal employment), the major occupational ISCO-88 group (nine occupation dummies), and also aggregated industry group where the individual is employed (four dummies, see Appendix A). *Family component* includes marital status and presence of children. Since our analysis spans over many years, I additionally include age, survey year and birth cohorts as controls.

[4]The analysis in this section utilizes Ben Jann's Stata implementation of the Oaxaca-Blinder decomposition method. See Jann (2008), for a slightly outdated (but informative) reference on this.

Table 8. Oaxaca-Blinder Decomposition of Gender Gap in Mean Job Level, for age groups 25-30 and 31-35.

	Age Window: 25-30		**Age Window: 30-35**	
Explained by Characteristics		**% of Gap Explained**		**% of Gap Explained**
Education Component	-0.0194***	15.69%	0.0471***	37.09%
Work Exp. Component	0.0156***	-12.58%	0.0182***	14.37%
Job Component	-0.1139***	92.00%	0.0085	6.72%
Family Component	0.0010	-0.81%	-0.0034***	-2.71%
Age	0.0050	-4.06%	-0.0002	-0.17%
Birth Cohort	0.0052	-4.23%	0.0042	3.34%
Year	-0.0107	8.61%	-0.0066	-5.21%
Total Explained	-0.1171***	94.61%	0.0678***	53.43%
Total Unexplained	-0.0067	5.39%	0.0591***	46.57%
Total Gap	-0.1238***	100%	0.1269***	100%

*** p<0.01, ** p<0.05, * p<0.1

Table Notes: The decomposition is based on SOEP waves 1984-2015. Sample includes dependent private-sector employees aged 25 to 55 with employer size 10 or larger. Entries are the male-female differential in the indicated variables multiplied by the male coefficients for the corresponding variables.

Our key results are as follows. The average gender gap in job levels rises over the life cycle. During the start of workers' careers, women are at a slightly higher level, leading to a negative gap. However by the next stage of the life cycle (ages 30-35), this gap reverses and becomes positive. Over the next two stages of the life cycle, the gap continues to increase. During ages 25-30, the (negative) gap can almost fully be explained by gender differences in characteristics (94%). However, starting from ages 30-35, around 40-47% of the gender gap in mean job levels remains persistently unexplained.

For the first age window wherein the gap differs significantly from the later age windows, one concern may be that younger cohorts in our analysis could be driving the pattern observed. To address this, Appendix C provides a robustness check. I restrict the birth cohorts to those born before 1980. This removes the youngest cohorts from the analysis, whom we do not observe for later age windows. Our results are robust. In the first stage of the life cycle, almost all of the gap can be explained.

This result of a gap in career dynamics coming up around age 30-35 itself may not be surprising; however, since I account for presence of children in this decomposition, it is noteworthy that more than 40% of the gap remains unexplained. This suggests that even after accounting for education, work experience, job-related components and family circumstances, we see evidence of an unexplained gap. Over the life cycle, only education and work experience appear to explain a part of the total gap, job and family components do not account for a significant part, through all age windows.

One plausible explanation may be that this is consistent with the story of *statistical discrimination* by employers towards female employees. Anticipating that female workers

Table 9. Oaxaca-Blinder Decomposition of Gender Gap in Mean Job Level, for age groups 35-40 and 40-45.

	Age Window: 35-40		**Age Window: 40-45**	
Explained by Characteristics		**% of Gap Explained**		**% of Gap Explained**
Education Component	0.0900***	34.71%	0.1306***	39.77%
Work Exp. Component	0.0546***	21.04%	0.1033***	31.46%
Job Component	0.0187	7.20%	-0.0335	-10.20%
Family Component	-0.0071***	-2.73%	-0.0039***	-1.18%
Age	-0.0001	-0.06%	0.0004	0.11%
Birth Cohort	0.0018	0.71%	-0.0022	-0.66%
Year	-0.0041	-1.57%	-0.0014	-0.42%
Total Explained	0.1538***	59.30%	0.1933***	58.88%
Total Unexplained	0.1055***	40.70%	0.1350***	41.12%
Total Gap	0.2594***	100%	0.3282***	100%

*** p<0.01, ** p<0.05, * p<0.1

Table Notes: The decomposition is based on SOEP waves 1984-2015. Sample includes dependent private-sector employees aged 25 to 55 with employer size 10 or larger. Entries are the male-female differential in the indicated variables multiplied by the male coefficients for the corresponding variables.

around the age of 30-35 will not be fully participating in the labor force (take maternity leave, or shift to another job with family-friendly policies and so forth), employers may choose to not promote women in the 25-30 age window. On a similar note, Bronson and Thoursie (2018) show evidence that over and above the child penalty, the mere fact of being a woman also carries a penalty in promtions.

However, an important caveat to my results must be noted. For the *family component* in my analysis, I account only for the presence of children (in a static sense) in the decomposition. Dynamic effects of childbirth are not looked into in this analysis. Hence I refrain from arriving at any conclusive remarks about the portion of the gap that could be accounted for by family characteristics from my analysis. In addition, the negative sign on the gap is puzzling. Since we observed in the results from Table 4 that presence of children is negatively associated with the average job levels of women, whilst being positively related to men's job levels, that also complicates the interpretation of the gender gaps in the explanatory variables in an O-B decomposition context. As mentioned in Blau and Kahn (2017), this may be the reason why traditional O-B wage decomposition analyses in the literature do not control for presence of children.

It is possible that inclusion of dynamic effects of childbirth will decrease the portion of the unexplained gap that comes up around ages 30-35 and persists till at least 45. If we go back to our results from section 3.2, we noted that dynamic effects of childbirth appear to have a strong negative relation with women's career dynamics. This represents a caveat to my results. A decomposition of life cycle career dynamics that isolates the contributions of the four components I present here (education, work experience, job component and

family component), along with accounting for the dynamic effects of childbirth, will likely be a fruitful avenue for further research.

5 Conclusion

This paper presents a detailed study on worker heterogeneity in career dynamics. It utilizes survey (panel) data that allows for direct measurement of career ladder progression, and serves as a rich source of information on relevant background characteristics. The panel dimension of the data allows us to accumulate promotions and demotions for individuals, and visualize career progression profiles over the life cycle for various sub-groups of workers.

This thesis starts by documenting the existence of a gender gap in career dynamics in the German context. In studying the gap further, I look into the role of five relevant factors - part-time versus full-time work, effect of children, marital status, public and private sector differences, and industry of employment.

Our results suggest that part-time work explains a portion of the observed gender differences in career dynamics. For children, we note strong (albeit not demonstrably causal) evidence of dynamic effects of childbirth playing an important role on women's career dynamics. In addition, presence of children is associated negatively with women's careers, but positively for men. Marital status itself appears to not have a (conditional) effect on career dynamics, the large differences for married men and women appear to largely be operating through other related channels (part-time work, occupational sorting and presence of children). A study into public and private sector differences reveal the former does not offer a premium strictly in promotion-rate terms. But through stronger career starts, workers in the public sector nevertheless are on average at a higher level on the career ladder than their private sector counterparts. Finally, I provide some preliminary evidence on the role of industries in differential career progression by gender.

Oaxaca-Blinder decompositions at different stages of the life cycle reveal an unexplained gap in career dynamics (within private sector workers) emerging around the age of 30-35. This is observed even after accounting for the aforementioned factors. This hints towards possible statistical gender discrimination in the labor market, however, it must be noted that dynamic effects of childbirth (not accounted for in the decomposition) may have an explanatory role to play in this regard. Future research may look into quantifying this aspect.

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6 Appendices

6.1 Appendix A: Aggregation of Industry Groups

The SOEP data provides information on industry of employment at the individual level using the NACE industrial classification (2-digit codes). In my analysis, this 2-digit classification has been aggregated further into four broad industry groups - *i) Primary, Construction and Transportation*, *ii) Manufacturing*, *iii) Education, Health, and Public Administration* and *iv) Other Services*, as follows:

1. Primary, Construction and Transportation:
    - Agriculture, commercial hunting
    - Forestry
    - Fishing, fish farming
    - Coal mining, peat extraction
    - Extraction of crude oil, natural gas
    - Mining of uranium and thorium ores
    - Mining of ores
    - Mining of stone, earth, and other minerals
    - Recycling
    - Power supply, utilities
    - Water supply
    - Construction
    - Wholesale and retail trade, repair of motor vehicles and motorcycles
    - Wholesale trade and commission trade
    - Land transport, transport in pipelines
    - Shipping
    - Aviation
    - Auxiliary transport services
2. Manufacturing:
    - Food processing industry
    - Tobacco processing
    - Textiles
    - Clothing
    - Leather and footwear

- Manufacture of wood and wood products
- Paper industry
- Publishing, printing and reproduction
- Coke, mineral oil, cracking, brewing
- Chemical industry
- Rubber and plastic products
- Manufacture of other non-metallic mineral products
- Manufacture of basic metals
- Manufacture of fabricated metal products
- Mechanical engineering
- Manufacture of office machinery, computers
- Electrical machinery
- Radio, television and communication equipment
- Manufacturing of Medical, Precision And Optical Instruments
- Vehicle construction, automotive industry
- Other vehicle construction
- Furniture, jewellery, musical instruments
- Other manufacturing

3. Education, Health, and Public Administration:

    - Public Administration and Defense; Compulsory Social Insurance
    - Education
    - Health, veterinary and social services

4. Other Services:

    - Retail trade, except motor vehicles, service stations
    - Hotels and restaurants
    - Post and telecommunications
    - Financial intermediation
    - Activities Auxiliary To Financial Intermediation
    - Real estate, renting and business activities
    - Renting of machinery and equipment
    - Computer and related activities

- Research and development
- Other Business Activities
- Sewage, solid waste disposal
- Interest contracts, religious associations
- Cultural, sporting and entertainment activities
- Other service activities
- Private households
- Industry - not further classified
- Craft trades - not further classified
- Services - without further allocation
- Extra-territorial Organizations and Bodies

6.2 Appendix B: Ordered Probit Estimates

The tables below correspond to ordered probit results of Tables 4 and 7 in the main paper. The coefficients cannot be interpreted directly. This serves as a verification of the direction and significance of the estimates in the main paper. Coefficients of individual fixed effects specifications are not reported since they cannot be estimated with ordered probit models.

Table 10. Average Job Level and Presence of Children, estimated separately for Women and Men, Ages 25-45.

Dep. Variable: Job Level	Women (1)	Women (2)	Men (1)	Men (2)
Have at least one child (indicator)	-0.185***	-0.102***	0.616	0.1315***
	(0.0372)	(0.0241)	(0.0343)	(0.0240)
Basic controls	Yes	Yes	Yes	Yes
Broad controls	No	Yes	No	Yes
R-squared	0.308	0.585	0.600	0.602
N	37,474	37,474	48,589	48,589

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions are based on SOEP waves 1984-2015. Sample includes dependent private-sector employees aged 25 to 45 with employer size 10 or larger. Basic controls (Women (1) and Men (1) columns) include educational level indicator (ISCED 1997 classification), years of work experience (both in full-time and part-time), as well as indicators for age, marital status, survey year and birth cohort. Broad controls (columns 2) add dummies for major occupational group (1-digit ISCO-88 classification) and broad industry group (see details in Appendix A).

Table 11. Estimates of Public-Sector Premium on Job Level, estimated separately for Women and Men.

Dep. Variable: Job Level	Women(1)	Women(2)	Women(3)	Men(1)	Men(2)	Men(3)
Public Sector (indicator)	0.328*** (0.0154)	0.059** (0.0149)	-	0.380*** (0.0182)	0.259*** (0.0196)	-
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Broad controls	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes
R-squared	0.375	0.620	-	0.407	0.610	-
N	85,038	85,038	-	103,794	90,636	-

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions are based on SOEP waves 1984-2015. Sample includes all dependent public and private sector employees aged 25 to 55 with employer size 10 or larger. Basic controls (Women (1) and Men (1) columns) include educational level indicator (ISCED 1997 classification), as well as indicators for age, marital status and survey year. Broad controls (columns (2)) add years of work experience (both in full-time and part-time), indicators for major occupational group (1-digit ISCO-88 classification), birth cohorts and for presence of children. Columns (3) add individual fixed effects.

6.3 Appendix C: Oaxaca-Blinder Decomposition with Restricted Birth Cohorts

Table 12. Oaxaca-Blinder decomposition for age window 25-30, restricted sample.

	Age Window: 25-30	
Explained by Characteristics		**Percentage of Gap Explained**
Education Component	-0.0151***	11.10%
Work Exp. Component	0.0230***	-16.92%
Job Component	-0.1376***	101.20%
Family Component	0.0016	-1.16%
Age	0.0066	-4.87%
Birth Cohort	-0.0001	0.04%
Year	-0.0064	4.71%
Total Explained	-0.1279***	94.10%
Total Unexplained	-0.0080	5.90%
Total Gap	-0.1360***	100%

*** p<0.01, ** p<0.05, * p<0.1

Table Notes: The decomposition is based on SOEP waves 1984-2015. Birth cohorts are restricted to those born before 1980. Sample includes dependent private-sector employees aged 25 to 55 with employer size 10 or larger. Entries are the male-female differential in the indicated variables multiplied by the male coefficients for the corresponding variables.

This shows that the main results of section 4 are not driven by inclusion of younger birth cohorts in our decomposition.

Affidavit

"I hereby confirm that the work presented has been performed and interpreted solely by myself except for where I explicitly identified the contrary. I assure that this work has not been presented in any other form for the fulfillment of any other degree or qualification. Ideas taken from other works in letter and in spirit are identified in every single case."

Place, Date	Signature